# CS-SENSE Reconstruction Using a Two-level Variable Density Sampling Pattern

**M. Doneva[1,2], P. Börnert[1], and A. Mertins[2]**
[1]Philips Research Europe, Hamburg, Germany, [2]University of Luebeck, Luebeck, Germany

**Introduction**: The synthesis of compressed sensing (CS) [1,2] and parallel imaging bears considerable potential for highly accelerated MR imaging. Several publications [3-6] have proposed a combination of SENSE and CS as an iterative sparsity-constrained SENSE reconstruction using variable density random sampling. The two-step method proposed by Liang et al. [7], which first performs CS to obtain aliased images and then applies Cartesian SENSE to obtain the final image, shows improved results compared with other methods. However, in this method, the intermediate aliased images exhibit reduced sparsity, compromising the CS reconstruction. Furthermore, potential errors in the CS reconstruction can be amplified in the SENSE reconstruction, especially in areas of high g-factors. In this work, we propose a two-step CS-SENSE reconstruction, in which the two reconstruction steps are used to recover distinct parts of k-space data and apply a two-level variable density sampling pattern.

**Methods:** CS and SENSE rely on different scan acceleration principles and apply different sampling patterns. CS exploits signal sparsity and requires incoherent sampling pattern. In SENSE, the acceleration is determined by the properties of the coil array and uniform sampling is usually employed. Several different sampling patterns (Poisson disk [8], golden ratio [9], and Halton sampling [10]) have been proposed as a compromise between uniform and random sampling for a CS-SENSE reconstruction, usually in combination with variable density sampling. However, this compromise is not necessarily optimal.

CS-MRI usually exploits image sparsity in the wavelet domain. However, the sparsity is not the same at all wavelet scales. Typically, the coarse scale wavelet coefficients (low frequencies) contain most of the signal energy and are much denser than fine scale coefficients. In terms of k-space, the center corresponds to a dense image, which contains most of the signal energy, and the periphery is the source of sparsity. This prior knowledge is usually exploited using variable density sampling, in which the central k-space is fully or almost fully sampled and the periphery is randomly undersampled. Thus, CS exploits mostly the sparsity of the high frequency data. SENSE, on the other hand, relies on low resolution coil sensitivity information, which is acquired in a reference scan. Thus, the limited resolution of the coil sensitivity information may cause errors in the reconstruction of high frequency information. However, SENSE can be applied to accelerate the central k-space.

Based on these observations, we propose a hybrid, two-level sampling scheme (Fig.1). The central part of k-space is uniformly undersampled by a factor determined by the coil geometry. The periphery is pseudo-randomly undersampled with a higher undersampling factor.

The following two-step reconstruction is applied. First, the missing data in the k-space center are recovered using SENSE. Then, the high resolution data are recovered in an iterative CS reconstruction by solving the constrained optimization problem:

$$f(x) = \sum_i \left\|S_i F_u x - y_i\right\|_2^2 + \left\|\Psi x\right\|_1,$$

where $F_u$ is the undersampled Fourier transform, $y_i$ and $S_i$ are the k-space data and the coil sensitivity for a coil i, and $\Psi$ is the sparsifying transform. In this second step, only the high resolution data are updated. Splitting the reconstruction in two sub-problems has the advantage that each of the sub-problems is better conditioned than a combined CS-SENSE reconstruction, in which CS and SENSE are performed simultaneously on the complete data.

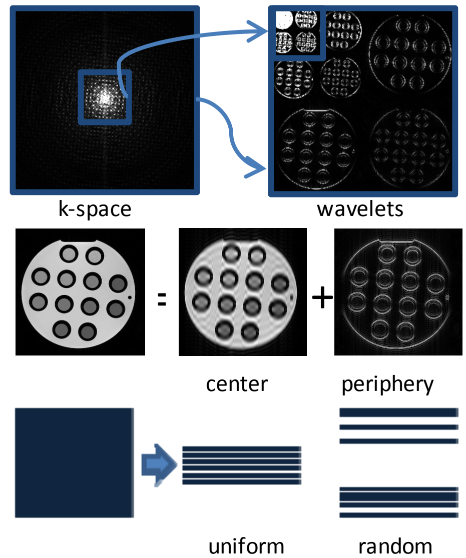


***Figure 1**. The correspondence between sparsity and k-space location and the proposed sampling are schematically shown. The high frequency part is very sparse, which is favorable for CS. Undersampling in the low frequency part, which is dense, can be achieved by SENSE.*

**Results:** Phantom and in vivo data were acquired on a 1.5T clinical scanner (Philips Healthcare, Best, The Netherlands) using an 8 element head coil. The following parameters were used: 1) phantom TE/TR = 5/1000ms, FOV = 250mm$^2$, 256x256 matrix and 2) in-vivo TE = 20ms TR = 500ms, FOV = 250mm$^2$, 256x256 matrix. Coil sensitivities were obtained from a separate reference scan. Full data sets were acquired and retrospectively undersampled according to the proposed two-level sampling scheme. The central 32 phase encoding lines were uniformly undersampled with a reduction factor of 2. The k-space periphery was randomly undersampled using Poisson disk sampling.

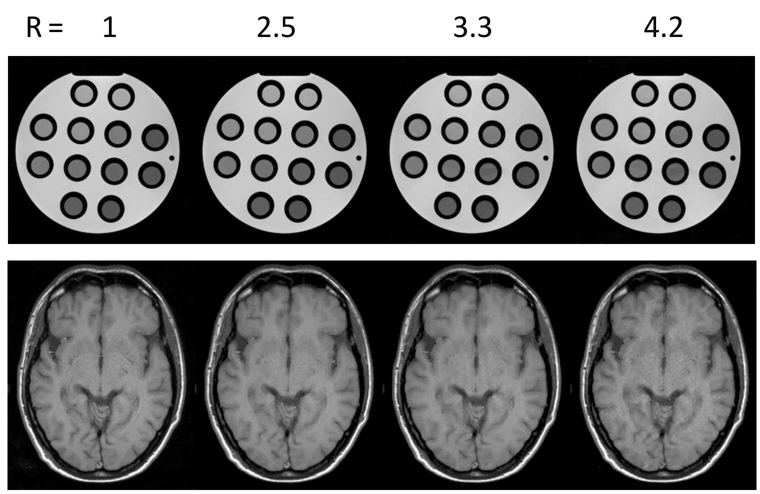


***Figure 2**. CS-SENSE two step reconstruction. Reconstruction results for the phantom and in-vivo data are shown for full sampling (R=1) and undersampling factors of 2.5, 3.4 and 4.2. No aliasing artifacts are visible, that would be present in SENSE at R >2*

Images were reconstructed with the two-step CS-SENSE applying Daubechies 4 wavelets in step 2 of the algorithm. Reconstruction results for different undersampling factors are shown in Fig. 2. The reconstruction time was 23s (30 iterations) for the brain data and 39s for the phantom (2.2 GHz CPU, 2GB memory, Matlab). Very good image quality was obtained for both the phantom and in vivo data even at acceleration factor of 4.2. In comparison, using SENSE-only reconstruction shows artifacts for acceleration factor greater than 2.

**Conclusion:** A novel method for CS-SENSE reconstruction is proposed, which applies two-level sampling pattern, motivated by the different mechanisms for scan acceleration in CS and SENSE. The two-step reconstruction results in improved conditioning of the reconstruction problem and avoids error propagation between the two reconstruction steps.

**References:** [1] Candes E et al, IEEE Tran Info Theo 2006, 52: 489-509; [2] Donoho D, IEEE Tran Info Theo 2006 ,52: 1289-1306; [3] Lustig M et al, MRM 2007, 1182-95; [4] Wu B *et al*, ISMRM 2008; #1480 [5] King K et al, ISMRM 2008; #1488. [6] Liu B *et al*, ISMRM 2008; #3154 [7] Liang et al. MRM 2009, 1574-84; [8] Dunbar D Proc SIGGRAPH 2006 503-508 [9] Winkelmann et al, Trans Med Imag 26:68-76 [10] Chan R, ISMRM Workshop on Data Samp Im Recon 2009.